Adaptation of Spiking Neural Networks for Image Clustering

Miss.Chinki Chandhok, Mrs.Soni Chaturvedi
Department of Electronics and Communication Engineering
Priyadarshini Institute of Engineering and Technology, Nagpur
Nagpur University, India

***Abstract*-A Biological Neural Network or simply BNN is an artificial abstract model of different parts of the brain or nervous system, featuring essential properties of these systems using biologically realistic models. The process of segmenting images is one of the most critical ones in automatic image analysis whose goal can be regarded as to find what objects are presented in images. This paper depicts the image processing algorithms that treat the problem of image segmentation. Spiking Neuron Networks (SNNs) are often referred to as the 3rd generation of neural networks which have potential to solve problems related to biological stimuli. Spiking neural networks (SNNs) exhibit interesting properties that make them particularly suitable for applications that require fast and efficient computation and where the timing of input-output signals carries important information. However, the use of such networks in practical, goal-oriented applications has long been limited by the lack of appropriate unsupervised learning methods. Image clustering in realistic human sense can very well be analyzed using SNN. Spiking neural networks usually results in improved quality of segmentation reflecting the mean square error to be minimum. Effective Matlab Programs yielded good results for real time, realistic human being brain behavior like output.**

Keywords- Spiking Neural Network (SNN), Spike; Integrate and fire neuron, Segmentation, backpropagation, gradient descent, wavelets

1. INTRODUCTION

Artificial neural networks (ANN) can broadly be classified into three generations. The first generation models consisted of McCulloch and Pitts neurons that restricted the output signals to discrete '0' or '1' values. The second generation models, by using a continuous activation function, allowed the output to take values between '0' and '1'. This made them more suited for analog computations, at the same time, requiring fewer neurons for digital computation than the first generation models [1]. One could think of this analog output between 0 and 1 as normalized firing rates. This is often called a rate coding scheme as it implies some averaging mechanism. Spiking neural networks belong to the third generation of neural networks and like their biological counterparts use spikes or pulses to represent information flow. Neurological research also shows that the biological neurons store information in the timing of spikes and in the synapses. Most of the success of the 2nd generation neural networks can be attributed to the development of proper training algorithms for them, e.g. the backpropagation algorithm [2-3]. It is one of the most widely known algorithms for training these networks and is essentially a supervised gradient descent algorithm. Due to the spiking nature of the biological neurons, traditional learning algorithms for rate-based networks aren't suitable for them. Also, the learning methods for these spiking networks are not as well developed as the traditional networks.

One commonly used unsupervised learning approach for spiking neural networks is called spike time dependent plasticity (STDP) [4-6]. It is a form of competitive Hebbian learning and uses spike timing information to set the synaptic weights. This is based on the experimental evidence that the time delay between pre- and post-synaptic spikes helps determine the strength of the synapse. Image segmentation consists of subdividing an image into its constituent parts and extracting these parts of interest. A large number of segmentation algorithms have been developed since the middle of 1960's, and this number continually increases at a fast rate. Simple and popular methods are threshold-based and process histogram characteristics of the pixel intensities of the image.

II. SPIKING NEURAL NETWORKS

Spiking neural networks (SNNs) are based on spiking neuron models and plasticity synapses. In general a spiking neuron operates by integrating spike responses from presynaptic neurons and generating an output spike when the membrane potential reaches a threshold value. Spiking Neuron Network (SNN) are often referred to as the 3rd generation of neural networks which have potential to solve problems related to biological stimuli [13-14]. They derive their strength and interest from an accurate modeling of synaptic interactions between neurons, taking into account the time of spike emission. SNNs model the precise time of the spikes fired by a neuron, as opposed to the conventional neural networks which model only the average firing rate of the neurons. Based on dynamic event-driven processing, spiking neuron networks open up new horizons for developing models with an exponential capacity of memorizing and a strong ability to fast adaptation [7].

Many of the existing segmentation techniques, such as supervised clustering use a lot of parameters which are difficult to tune to obtain segmentation where the image has been partitioned into homogeneously colored regions. In

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this paper, a spiking neural network approach is used to segment images with unsupervised learning. The paper is organized as follows: in first Section, related works in literature of spiking neural Networks are presented. The second Section is the central part of the paper and is devoted to the description of the SNN segmentation method and its main features. Simulation of neuron model and its training are reported in the third Section. The fourth section describes the proposed method of segmentation. Results and conclusion are discussed in the last section. This paper depicts how SNN can be applied with efficacy in image segmentation**.**

III. NEURON MODEL AND TRAINING

There are many different models one could use both to model the individual spiking neurons, and also the nonlinear dynamics of the system. Individual neuron models can be categorized according to their biological plausibility and speed. Generally speaking, the more biologically plausible models tend to require more computation time. The Hodgkin-Huxley (HH) [8] model was one of the first detailed neuron models developed, and they received a Nobel Prize for this work. Though the model is quite accurate, it is expensive to compute. Another rather simple model is the leaky integrate and fire (LIF) [9] model, which is much simpler and is computationally cheaper. Izhikevich [10] compares these and many more such models. We [11] have compared HH to LIF and found LIF to be at least 5000 times faster than HH. Even though the LIF model is computationally inexpensive, it can model the spike times very similar to the HH model. This is important as spiking networks often use the timing of spikes for learning.

A. Simulation of Leaky Integrate and Fire Model of SNN

While the LIF model has limited basis physiologically, its strength lies in its computationally simple ability to generate spike events with an input-driven frequency.

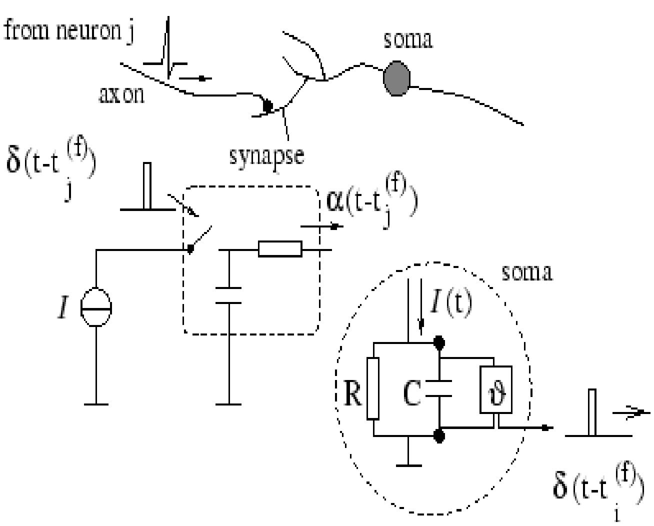

Fig1. LIF Model of Spiking Neural Network

Currently most spiking neural network models for segmentation and recognition of objects are based on leaky integrate-and fire neuron models and the principle of segmentation is based on neural oscillators. In this paper, a conductance based integrate-and-fire neuron model is employed so that the more biological neuronal behaviors can be reflected in the network models.

Parameters	Typical Values
T	50 Milliseconds
dt	0.125 Milliseconds
I	1.5 Milliampers
R_m	1000 kilo-ohms
C_m	10 Microfarads
τ_ref	4 Milliseconds
V_{th}	1Volt
V_spike	0.5 Volts
t_rest	0

Table1. Typical values for LIF neuron model

T is the total time required to simulate, dt is the simulation time step, I is the input current in milliampers, R_m and C_m are membrane resistance and capacitance respectively. τ_ref is the refractory period, V_{th} is the spike threshold in volts, V_spike is the spike delta in volts, t_rest is the initial refractory time. The minimal distance between two spikes defines the absolute refractory period of the neuron. The absolute refractory period is followed by a phase of relative refractoriness where it is difficult, but not impossible to excite an action potential [19]. Using all of the above mathematical parameters defined in table1, we have successfully simulated Leaky Integrate and Fire Model of SNN. We found that when the membrane potential of a neuron exceeds the threshold value, a spike or pulse is generated which is transmitted to other neurons. Simulation results show that spike is generated at the membrane potential of 1.5volts. Long and Gupta [12] showed that this method is about 10,000 times faster than solving the H-H equations, but yet the solution is often quite similar.

B. Training of Spiking Neural Networks

One of the key problems with spiking neural networks is the training algorithm. Much research relied on biologically inspired local learning rules, but these rules can only be implemented using unsupervised learning. However, in supervised learning Spike Prop algorithm operates on networks of spiking neurons that use exact spike time temporal coding. This means that the exact spike time of input and output spikes encode the input and output values (Bohte et al., 2000). Spike Prop is an error-back propagation learning rule suited for supervised learning of spiking neurons that use exact spike time coding. Spike Prop assumes a special network topology. Globally the network looks like a classical feed forward network, but every connection consists of a fixed number of delayed synaptic terminals, different weights and different delays. However, the delays are fixed, and only the weights can be trained. Because the delayed synaptic terminals are fixed, this network topology has to be largely over-specified to make all possible weight/delay combinations possible (Natschlager and Ruf, 1998). Enhancements to the Spike Prop algorithm such that, the delay and the time constant of every connection and the threshold of the neurons can be trained; because the delays can be trained, fewer synaptic terminals are necessary, effectively will reduce the number of weights and thus, the simulation time of the network.

IV. PROPOSED METHOD

There are variety of approaches are available for image segmentation. In this paper, the fuzzy and the neural network aspects are enumerated. The proposed architecture is feed forward, but unlike the conventional MLP the learning is unsupervised. In recent years there has been a growing interest in developing effective methods for content-based image retrieval. Image clustering and categorization is a means for high-level description of image content. The goal is to find a mapping of the archive images into classes (clusters) such that the set of classes provide essentially the same information about the image archive as the entire image-set collection. The generated classes provide a concise summarization and visualization of the image content that can be used for different tasks related to image database management. Image clustering enables the implementation of efficient retrieval algorithms and the creation of a user-friendly interface to the database.

In the proposed work, we have implemented image clustering using any classical technique such as k-means clustering. The proposed technique has been applied to a brain Image. First we have chosen an image of sectional view of brain defined in pixel grid of 256 x 256. SNN is then applied with unsupervised learning on the same sample image. K-means clustering is used to group the pixels of the image into several clusters. Pixels of the image are divided into 8*8 matrix blocks and a feature vector is extracted for each block of pixels. A label or index is assigned to each feature vector and the colour assignment to each block of pixel is done based on this index. Using the function k-means, five iterations are performed to form five clusters of different colors. Finally, a segmented image is obtained using k-means clustering. Further, neural approaches have been applied for image segmentation which is being discussed in the next section.

V. NEURAL APPROACHES TO SEGMENTATION

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each pixel in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. In the proposed work, the feed forward neural networks are initialized and trained with faster back-propagation algorithm. The algorithm we have used to train the network is the Backpropagation Algorithm. The general idea with the backpropagation algorithm is to use gradient descent to update the weights so as to minimize the squared error between the network output values and the target output values. The update rules are derived by taking the partial derivative of the error function with respect to the weights to determine each weight's contribution to the error. Then, each weight is adjusted, using gradient descent, according to its contribution to the error. The various features extracted from the image are assigned as the input patterns to the ANNs. To create a network that can handle noisy input vectors, it is best to train the network on both ideal and noisy vectors. The selection of a learning algorithm and parameters such as number of neurons, number of layers, and the transfer functions, determine the accuracy of the network, resulting in complex architectures to solve the problem [18].

Network is first trained on ideal vectors until it has low sum squared error. All training is done using back-propagation with both adaptive learning rate and momentum with the function trainbpx. An optional parameter is defined to set the number of epochs between feedbacks during training. Finally a trained network is created. This trained network is further simulated. The concept of wavelets has been used for feature extraction. In the proposed work, we adapted 5000 epochs for training the network and the progress display is shown after every 20 epochs. Finally the trained network is tested for errors. At last, the MSE is calculated for both ANN and SNN. Simulation results show that the MSE error is minimized with Spiking Neural Networks compared to Artificial Neural Networks.

VI. SIMULATION RESULTS

A. Results of Spike Generation

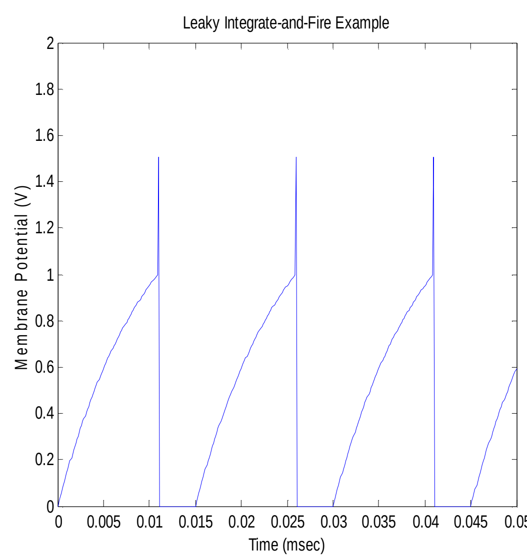

Fig 2. Simulation of LIF Model of SNN

Simulation results show that a spike is generated at 1.5V. Hence it is clear that when the membrane potential of a neuron reaches a threshold value i.e. 1, a spike or pulse is generated which is passed on to other neuron. The LIF model is one of the most widely used in computational neuroscience. One of the reasons for this is that it is the easiest to implement. Its model is so simple that the computational cost is minimum compared against other spiking neuron models [20].

B. Segmentation Results

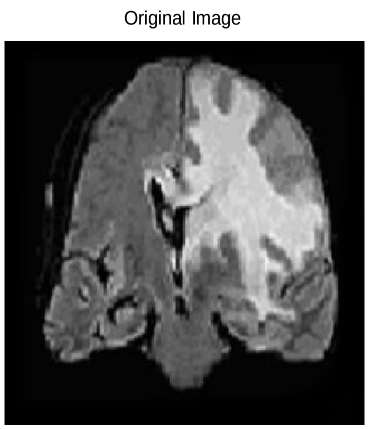

Fig 3. Original image of brain2.jpg

Figure 4 shows the formation of five different clusters using k-means clustering algorithm. It is actually a mapping which shows how clusters of different colors are seperated from one another and how close the clusters are from one another.

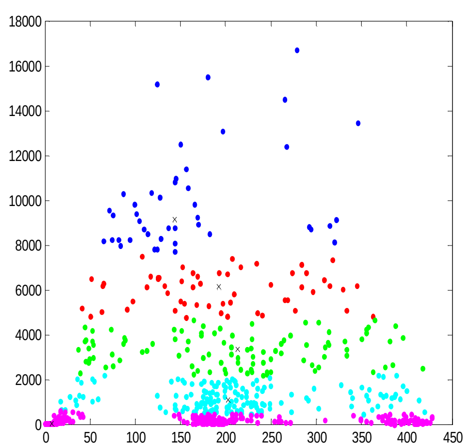

Fig.4. Formation of 5 clusters

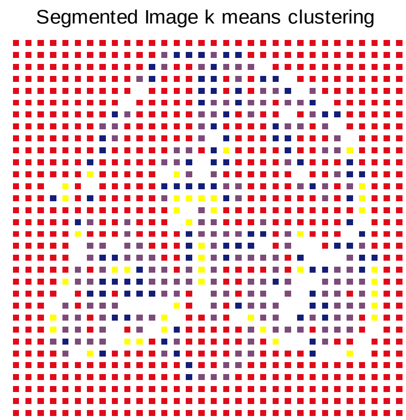

Fig 5. Segmented image of brain2,jpg with K-Means

Figure 5 represents the segmented image obtained using k-means clustering. It is clearly seen that red colour blocks of pixels are more in frequency compared to yellow, blue, purple and white color blocks. Also, the blocks of different colors are clearly discriminated from one another. It is possible to count the number of blocks of different colors.

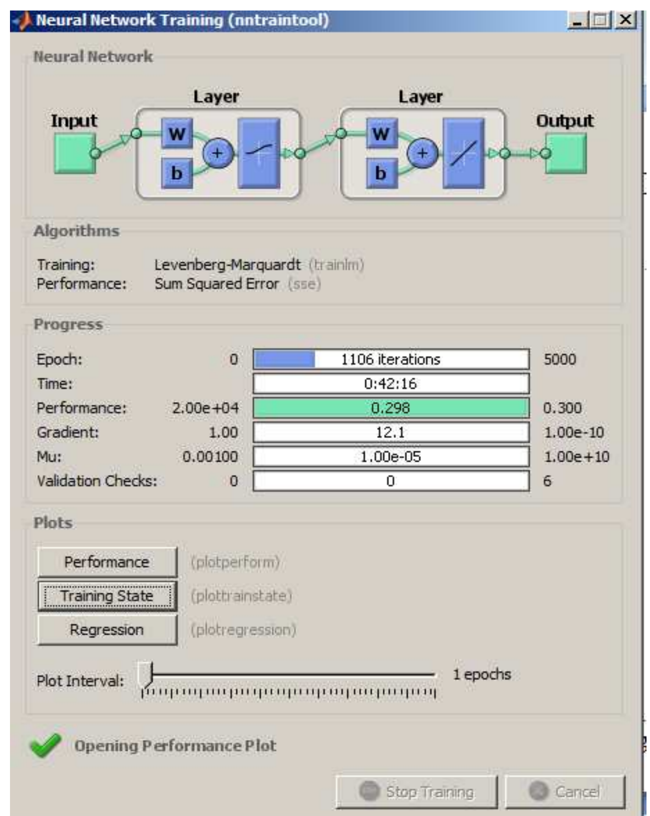

Fig 6.Training of Neural Network with Levenberg-Marquardt Algorithm

Figure 6 shows the training of feed forward neural network with back-propagation algorithm. The neural network took 1106 iterations to meet the performance goal. Network goal is kept minimum for good accuracy.

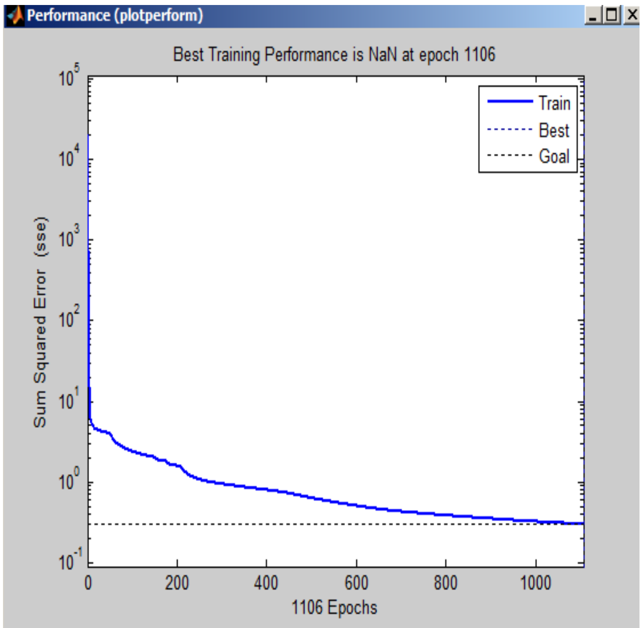

Fig 7.Plot of sum squared error versus number of epochs.

Figure 7 shows the graph plotted between Sum squared error and number of epochs. It is seen that as the number of epochs increases the sum squared error decreases and the performance goal was meet after 1106 iterations and the neural network took about 42 minutes and 16 seconds to train itself.

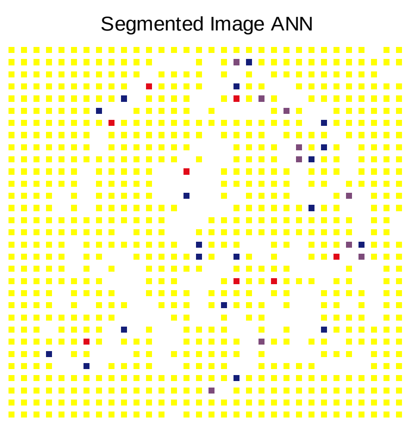

Fig 8 Segmented image of brain2.jpg with ANN

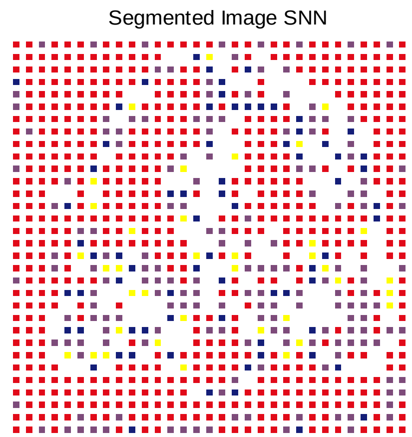

Fig9. Segmented image of brain2.jpg with SNN

Figure 8 shows the segmented image obtained with ANN. It is seen that only the yellow and white colour blocks are recognized by ANN most of the times. Also the frequency of yellow color blocks are more compared to the purple, blue, red, white color blocks. Hence, the clusters of different colors are not clearly discriminated in the segmented image obtained with ANN. Figure 9 shows the segmented image obtained with SNN. This image closely resembles the segmented image obtained with k-means. Also, the frequency nature of clusters is preserved and clusters of different colors are easily discriminated from one another.
It is clear that with the K-means algorithm, one may get some faulty segmented pixels while the use of neural network techniques may increase the performance but some errors might remain. Spiking neural networks usually results in improved quality of segmentation reflecting the mean square error to be minimum**.** SNNs have emerged as a paradigm that more accurately model the biological functions of the human brain, offering the potential to re-create more biologically plausible computing systems [17].

C. MSE Calculation

Parameters	Typical Values
R	2
Q	1024
S1	400
S2	1
MSE (ANN)	51.2695
MSE (SNN)	1.4063

[R,Q] denotes the size of the input patterns to the ANN and [S2,Q] denotes the size of targets, S1 is the number of hidden neurons.

Mean square error with ANN is the difference between the blocks of pixels of segmented image obtained with ANN and the segmented image obtained with K-means. Mean square error with SNN is the difference between the blocks of pixels of segmented image obtained with SNN and the segmented image obtained with K-means. Mean square error has been reduced from 51.2695 in case of ANN to 1.4063 with SNN.

CONCLUSION

In the current work, we have reviewed some existing methods of segmentation based on clustering and neural networks. MLF neural networks are very robust,i.e. their performance degrades gracefully in the presence of increasing amounts of noise .The big problem is the fact that ANNs cannot explain their prediction, the processes taking place during the training of the network are not well interpretable and this area is still under development [15,16].The number of weights in an ANN is usually quite large and time for training the ANN is too high. The approach uses wavelet decomposition to perform clustering at increasingly finer levels of decomposition. Wavelet based clustering is unsupervised one and give good results for the effective feature extraction. Table 2 shows the calculated values of mean square error for the sample image brain2.jpg. It is clear that amongst all the segmentation methods used, an improved quality of segmentation is obtained with the third generation spiking neural networks reflecting the mean square error to be minimum.

After training, we observed that input patterns, which belong to the same class, generate almost the same firing rates (low standard deviation) and input patterns, which belong to different classes, generate firing rates different enough (average spiking rate of each class widely separated) to discriminate among the different classes. In this paper we applied spiking neural networks to image segmentation. Results of SNN are quite realistic and easily depend on biological activity of brain signals. .The computational cost of LIF model is low compared to the feed-forward network of ANN [20]. It has been proved that spiking neurons can be considered as an alternative way to perform different pattern recognition tasks. Image Clustering using k-means also proved better logic for assigning indexes to clusters effectively.

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